

An Investigation of Information Alignment and Collaboration as Complements to Supply Chain Agility in Humanitarian Supply Chain

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Abstract

Our study examines the relationship between information alignment (IA), collaboration (CO) and supply chain agility (SCAG) under the moderating effects of artificial intelligence driven big data analytics capability (AI-BDAC) and intergroup leadership (IGL). We have grounded our theoretical model in the resource based view (RBV) and contingency theory and further tested our research hypotheses using multi-informant data collected using a web-based pre-tested instrument from 613 individuals working in 193 humanitarian organisations drawn from 24 countries located on various continents across the globe. We tested our research hypotheses using variance based structural equation modelling (PLS-SEM). Our study offers interesting results which help to advance the theoretical debates surrounding technology-driven supply chain agility in the context of humanitarian settings. We further provide some directions to managers engaged in disaster relief operations, who are contemplating using emerging technologies to enhance collaboration and supply chain agility. Finally, we have outlined the limitations of our study and offer some future research directions.

Key-words: Information Alignment, Artificial Intelligence, Big Data Analytics, Intergroup Leadership, Supply Chain Agility, Humanitarian Supply Chain, Humanitarian Operations, Pandemics, Empirical Study

1. Introduction

The humanitarian supply chains providing disaster relief are often compromised due to lack of visibility, an absence of information sharing, a lack of trust among disaster relief workers and poor collaboration (Swanson and Smith, 2013; Nurmala et al. 2018; Larson and Foropon, 2018; Dubey et al. 2019a,b; Duong and Chong, 2020). Indeed, in their recent studies, scholars found that from the Indian Ocean Tsunami, the Haiti Earthquake, the Ebola outbreak in West Africa, through to the recent COVID-19 pandemic, the disaster relief workers on the ground commonly identify a lack of visibility, poor information sharing and poor leadership as important constraints to effective operations (Altay and Pal, 2014; Dubey et al. 2019a; Salem, 2019; Ivanov, 2020a,b; Ivanov and Dolgui, 2020 a,b). In the dynamic and highly uncertain environment, enhancing the collaboration among the

disaster relief workers holds great promise in terms of resolving issues that may hinder disaster relief workers' abilities to productively share their strategic resources in the form of activities and information (see, Balcik et al. 2010; Jahre and Jensen, 2010; McLachlin and Larson, 2011; Akhtar et al. 2012; Altay and Pal, 2014; Kabra and Ramesh, 2015; Prasanna and Haavisto, 2018; Dwivedi et al. 2018; Schiffing et al. 2020a). The long term impacts of these disasters may be attributed to the poor information exchange and lack of collaboration among the disaster relief workers, who are dealing with situations that are often characterised by highly dynamic and uncertain task environments (Chen et al. 2013; Fan et al. 2019; Dubey et al. 2020a; Dolgui et al. 2020b; Queiroz et al. 2020a; Ivanov, 2020b; Dubey et al. 2020; Fosso Wamba and Queiroz, 2020; Schiffing et al. 2020b).

The existing academic literature focusing either on the role of IT or ICT's capabilities in the context of disaster relief efforts or on the management of humanitarian supply chains (see, Ragini et al. 2018; Fosso Wamba et al. 2019; Akter et al. 2019; Sharma et al. 2020; Rodríguez-Espíndola et al. 2020) has gained significant attention. Chan and Reich (2007) further argue that the level or degree of alignment between IT capabilities and business strategy often differentiates successful organisations from less successful ones (Ivanov et al. 2020; Fragapane et al. 2020). However, despite a growing rich body of literature, empirical studies focusing on the criticality of information alignment (IA) and collaboration (CO) among disaster relief workers for supporting coordinated task performance in complex operational environments are scant (Li et al. 2011; Chen et al. 2019). Agility in humanitarian supply chains is considered a vital capability for disaster relief operations (see, Charles et al. 2010; Day et al. 2012; Dubey and Gunasekaran, 2016; Altay et al. 2018; Stewart and Ivanov, 2019). Moreover, collaboration is also considered as an important element in an agile supply chain network (Lee, 2004). It is further noted that the integration, change, competence, partnership and welfare have been considered determinants of supply chain agility (Jain et al. 2008). Whilst Moshtari (2016, p. 1542) argues that “*collaboration may occur over one or more tasks within humanitarian setting, for example information sharing, capacity planning, needs assessment, resource allocation, joint procurement, warehousing, transportation and last mile delivery*”. Hence, we argue that collaboration (CO) is an important element of supply chain agility (SCAG). Following Alvesson and Sandberg (2011) arguments, we attempted to address our research gaps of our study. However, the existing literature on humanitarian supply chain management remains silent in respect of the relationships between information alignment (Tan et al. 2010; Ng et al. 2013; Tarafdar and Qrunfleh, 2017; Dolgui et al. 2018), collaboration and supply chain agility. To address

this research gap, we posit our first research question (RQ1) as: *What are the distinct and joint effects of LA and CO on SCAG?*

Artificial Intelligence driven Big Data Analytics Capability (AI-BDAC) is an all-encompassing term for techniques destined to handle big data characterised in terms of high volume, velocity and variety (Queiroz and Telles, 2018; Dubey et al. 2020b), as well as encompassing challenges related to capture, storage, transfer & sharing, search, analysis, and visualisation of such data. Amongst the various challenges, especially critical ones are data capture, storage, transfer & sharing related to system architecture, and search, analysis, and visualisation related to data analytics methods (Srinivasan and Swink, 2018). The applicability of Big Data has been demonstrated to represent dynamic populations (Deville et al., 2014) and to understand population flows (Wang et al., 2018). The use of big data analytics in crisis situations has been advocated in literature (Akter and Wamba, 2019). However, it is evident that we lack standards and proper methods of data anonymisation and data fusion – such as utilising Artificial Intelligence (AI) to enrich and summarise the spatial data using different data sources – in order to use the full potential of Big Data at varying temporal and spatial scales and to get this information into practice. Improved scientific solutions enable the development of models of mobility flows, contacts between people and subsequent analyses revealing the societal and economic impact of a crisis, which are needed to monitor the recovery process (Poom et al. 2020). We note this as a research gap. Hence, to address this we posit as our second research question as (RQ2) as: *What are the effects of AI-BDAC on the paths connecting LA/CO and SCAG?*

Despite increasing disaster relief efforts, it is noted that international humanitarian organisations' (IHO) efforts reach less than half of the estimated affected populations and the beneficiaries' needs are not met effectively (Clarke and Campbell, 2018). Salem et al. (2019) argue that leadership is pivotal for improved humanitarian operations. In fact, operations management literature has recognised the need for effective leadership to achieve desired success (de Koster et al. 2011). However, the humanitarian operations management literature has remained silent on this front (Salem et al. 2019). As a result, the role of leadership on the use of emerging technologies for improving information alignment and collaboration among disaster relief workers is also not well understood. Hence, we suggest that in the context of disaster relief, "*intergroup leadership theory*" may offer useful insights to explain collaboration among members in humanitarian supply chains (Salem et al. 2019). Gooty et al. (2010) describe leadership as the process of directing and influencing the task-related activities of group members. Salem et al. (2019) further argue that leadership plays a crucial role during pre and

post disaster relief operations. Kent (2004) found that leadership has an important role to play in any organisational initiatives, through belief and participation. Although, we understand the role of effective intergroup leadership in humanitarian operations (Salem et al. 2019), it is not clear how intergroup leadership influences the effects of IA and CO on SCAG. We note this as a clear research gap. To address this research gap, we posit our third and final research question (RQ3): *what are the effects of intergroup leadership on the paths joining IA/CO and SCAG?*

We have organised our paper as follows. In section 2, we provide a brief synopsis of the underpinning theories of our study, namely: RBV and contingency theory/intergroup leadership, the theoretical model and research hypotheses. In section 3, we discuss our hypo-deductive research strategy, including our sampling design and data collection strategy, which resulted in data from questionnaires completed by 613 individuals working in 193 NGOs, UN agencies and other service providers involved in humanitarian disaster relief activities. We also report the results of non-response bias testing. In section 4, we present our data analysis, which involves using PLS-SEM to test our theoretical framework, with Warp PLS 6.0 utilised to address criticism of traditional PLS-SEM methods. We also report the results of testing the hypotheses in this section. Next, in section 5, we present a discussion of our results, focusing on the implications for theory and practice. In relation to theory development, we describe three main contributions of our study. We then set out implications for managers engaged in disaster relief, including how assumptions about the importance of interdependency and relationship duration to achieving agility, derived from research in other contexts, might not hold true in humanitarian supply chain settings. Finally, in section 6, we draw our conclusions, finishing by stressing how our study provides enhanced understanding of relationships between critical elements in humanitarian supply chains which can contribute to better management of disaster relief activities.

2. Theoretical Development and Hypotheses Formulation

There is increasing use of organisational theories to explain complex management situations (see, Ketchen and Hult, 2007; Gunasekaran et al. 2018). There are many popular organisational theories: resource based view; resource dependence theory; institutional theory; relational view; contingency theory; organisational information processing theory and many more. Ketchen and Hult (2007) emphasise the importance of organisational theories in the operations and supply chain management field. However, despite a rich body of literature on humanitarian operations management, the use of

organisational theories to explain some complex phenomena has received less attention in comparison to established management fields (Gunasekaran et al. 2018). Even, some scholars like Madhok (2002) have attempted to use a combination of one or more organisational theories in theory driven empirical studies. In the current study, we try to answer our research questions using a combination of two organisational theories: resource based view and contingency theory.

The RBV logic helps to understand how resources/ capabilities can be utilised to gain competitive advantage (Rumelt, 1984; Barney, 1991; Sirmon et al. 2011; Hitt et al. 2016). Resources can be classified as physical capital, human capital, technological capital, and reputational capital, being either tangible (e.g. infrastructure) or intangible (e.g. information or knowledge sharing) (Größler and Grübner, 2006). The bundling of different types of resources helps to generate competitive advantage (Newbert, 2007). Bundling has been defined by scholars (e.g., Grant, 1991; Sirmon et al., 2008) as resource integration to allow capability building, subsequently allowing for exploiting opportunities or mitigating threats (Sirmon et al. 2008). Whereas resources refer to the tangible and intangible assets, capabilities are subsets of a firm's resources which are non-transferable and aim at enhancing the productivity of other resources (Makadok, 1999). Hence, capabilities are identified as an absolute necessity for an organisation to prosper (Hitt, 2011). They depend on the environmental conditions in which an organisation operates (Brandon-Jones et al. 2014; Gunasekaran et al. 2017). Wu et al. (2006) argue that the utilisation of capabilities may help organisations to achieve or sustain competitive advantage, and, specifically in relation to supply chains, Wong and Karia (2010) identify the logistics resources acquired and bundled by logistics service providers to achieve competitive advantage.

Few studies have investigated the effect of the combination of resources and capabilities on performance (Brandon-Jones et al. 2014; Gunasekaran et al. 2017). Those which have include Ravichandran and Lertwongsatien (2005), who examined the influence of information resources and capabilities on organisational performance. In addition, Brandon-Jones et al. (2014) tested the impacts of supply chain connectivity and supply chain information sharing as resources and supply chain visibility as capability on the resilience and robustness of supply chains when developing inter-organisational relationships. Furthermore, Dubey et al. (2018) examined the effects of intra-organisational resources, in particular top management support and IT, on leveraging capabilities, e.g. for supply chain integration (see, Themistocleous et al. 2004).

In this study, we use RBV to conceptualise AI-BDAC as an organisational capability that impacts information alignment and collaboration. However, despite its popularity among operations management scholars (Hitt et al. 2016), the RBV has never looked beyond the properties of the resources and the resource markets to explain firm heterogeneity (Oliver, 1997). Ling-Yee (2007) further argues that RBV suffers from “context insensitivity”. Context insensitivity suggests that the RBV fails to provide a better explanation or identify the conditions in which resources or capabilities may be most valuable (Brandon-Jones et al. 2014). Eckstein et al. (2015) argue that contingency theory offers an alternative theoretical lens to examine the contingent conditions under which resources and capabilities can generate better value. Donaldson (2001) use contingency theory to explain how organisations must adapt depending on the environmental conditions in which they operate. Sousa and Voss (2008) discuss how contingency factors, including national context and culture, firm size, strategic context and other organisational variables, have been analysed in operations and supply chain literature. The factor of top management commitment has been identified as a key contingent factor (Dubey et al. 2018). Whilst some scholars have integrated contingency theory and RBV to address the limitations of the static nature of the RBV (see, Aragon-Correa and Sharma, 2003; Brandon-Jones et al. 2014; Eckstein et al. 2015; Dubey et al. 2018), it is well recognised within operations and supply chain literature that contingent perspectives of RBV are still underdeveloped (see, Brandon-Jones et al. 2014).

2.1 Theoretical Model

Our theoretical model has two key elements: RBV and contingency theory, with a specific use of intergroup leadership in respect of the latter of the two elements (see Figure 1). Building on this tradition, we seek to use RBV to explain how information alignment, collaboration and AI-BDAC impact supply chain agility. The alignment of information is recognised as a critical factor that supports the coordination of task performance in complex operational environments (Caldwell et al. 2008). Moreover, contingency theory provides an explanation as to how contingent factors like intergroup leadership influence the effects of the information alignment and collaboration on supply chain agility. Thus, based on these two theories: RBV and contingency theory (intergroup leadership), we develop our theoretical model.

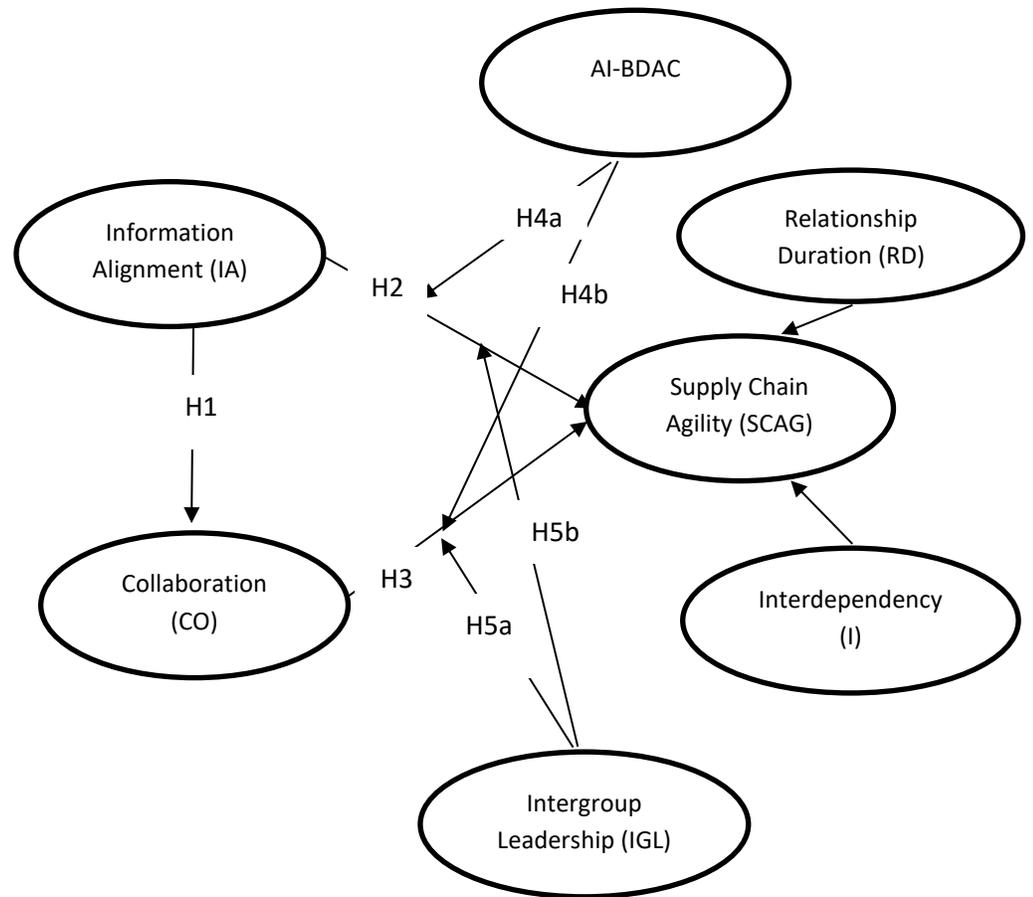


Figure 1: Theoretical Model

2.2 Research Hypotheses

2.2.1 Impact of Information Alignment on Collaboration

In complex environments like humanitarian operations, information sharing among disaster relief workers is often considered critical for better collaboration (Wentz, 2006; Altay and Pal, 2014; Altay and Labonte, 2014). Furthermore, organisations involved in humanitarian efforts that have high levels of transparency and effective information-sharing capabilities are significantly well positioned to develop and deploy systems and processes for supporting analytics capabilities (Prasad et al. 2019). In addition, organisations that invest in developing artificial intelligence driven big data analytics capabilities are likely to invest in supply chain visibility because visibility provides data upon which

analytics systems and processes operate (Dubey et al. 2019a; Akhtar et al. 2019; Dubey et al. 2020b). Tatham and Rietjens (2016) argue that for effective collaboration it is important to understand the roles, relationships, capabilities, motivations, and information-sharing needs in complex environments. Based on the existing literature on collaboration among humanitarian workers and IT-business alignment, we argue that the extent to which information communication technology (ICT) capabilities improve information transparency and real-time data/information exchange depends on the severity of the disasters and their effects on victims (Fan et al. 2019). Reich and Benbasat (2000, p. 82) define information alignment as “*the degree to which the information technology mission, objectives and the plans support and are supported by the business mission, objectives and plans*”. Kearns and Lederer (2003) argue that information alignment is a key predictor of IT investment profitability. In the context of supply chains, Tan et al. (2010, p. 378) define information alignment as “*the alignment of information flows and the use of compatible information systems between the buyer and supplier consistent with meeting strategic goals and customer requirements*”. We note that the literature focuses on resource (e.g., IT applications), operational enabler (e.g., business process reengineering), and strategic weapon (e.g., a deliberately planned contract that sets specific alignment targets) as the most important factors for achieving IT and operational integration (Chi et al. 2020). Chi et al. (2020) further argue that in order to maximise the benefit of relationship-specific IT investment, appropriate policies and procedures should be put in place to guide and govern IT-enabled collaborative activities. Thus, we can argue that information alignment improves collaboration (Simatupang and Sridhar, 2005; Li et al. 2011; Chi et al. 2020). Following these arguments, this study focuses on exploring how information alignment between humanitarian workers engaged in disaster responses impacts collaboration among the disaster relief workers. Hence, we expect organisations involved in humanitarian activities, such as disaster relief, to understand the connections between information alignment and collaboration. We hypothesise these connections as:

H1: Information alignment has positive and significant effect on collaboration.

2.2.2 Impact of information alignment and collaboration on agility

In recent years, information technology alignment has remained a top priority for humanitarian relief organisations (L’ Hermitte et al. 2016). Information alignment has a positive influence on agility (Tallon and Pinsonneault, 2011). Whether information alignment helps or hurts agility in humanitarian contexts is an unresolved issue (Fawcett and Fawcett, 2013). In this study, we intend to examine the relationship between information alignment and agility in humanitarian supply chains. Humanitarian

organisations are expected to make relationship-specific investment and reconfigure business processes to align not only with their internal business models but also with other organisation models to create a seamless disaster response mechanism. Information should flow freely between collaborative partners to streamline operations. Finally, humanitarian workers should also govern and formalise the relationship with explicit rules and procedures. Lee (2004) argues that collaboration is an essential element of supply chain agility and Moshtari (2016) posit that where there is diversity between disaster relief workers' characteristics i.e. in goals, motivations, the success of collaborative relationships often depends on the workers' level of understanding about each other's objectives, operations and values. Dubey et al. (2019a) found that emerging technology like big data analytics plays a significant role in improving collaboration in context to civil-military partnerships. Hence we argue that information alignment and collaboration are crucial elements of agility. We hypothesise these relationships as:

H2: Information alignment has positive and significant effect on agility.

H3: Collaboration has positive and significant effect on agility.

2.2.3 Moderating Role of Artificial Intelligence driven Big Data Analytics Capability (AI-BDAC)

Artificial Intelligence (AI) and Machine Learning (ML) offer new opportunities to use the big data that we already have, as well as unleash a whole lot of new uses with new data types (Akter et al. 2020; Ivanov and Dolgui, 2020; Dolgui et al. 2020a,b). Srinivasan and Swink (2018) argue that analytics capability enables firms to increase their information processing capability. Dwivedi et al. (2019) identify several positive impacts on extracting useful information from big data that AI driven big data analytics capability has, which includes trust building, more coordination in uncertain environment and better decision making. Akter et al. (2016) highlight the role played by BDAC in improving alignment between various functional strategies and organisational level strategy to achieve better performance in highly dynamic environment. Dubey et al. (2019a) found a positive association between big data analytics capability and collaboration among civil-military organisations engaged in disaster relief operations. Achieving a shared vision, managing shared expectations, facilitating collaboration, and sharing information are crucial for disaster relief operations (Altay and Labonte, 2014). However the moderating role of AI-BDAC on the paths joining information alignment/collaboration and the agility is an unresolved issue. Hence, we hypothesise it as:

H4a: AI-BDAC has positive and significant effect on the path joining information alignment and agility.

H4b: AI-BDAC has positive and significant effect on the path joining collaboration and agility.

2.2.4 The Moderating Role of Intergroup Leadership

Following the tenet of intergroup leadership (Hogg et al. 2012) we argue that managing disaster relief subgroups of diverse backgrounds to achieve desired levels of collaboration requires leaders to recognise and respect each disaster relief subgroup's identities. In order to achieve desired levels of collaboration among distinct subgroups engaged in disaster relief operations, effective leaders engage in subgroup leadership, which refers to leading distinct subgroups. Such leaders understand that maintaining a positive subgroup identity requires a successful relationship with the respective subgroup (Hogg et al. 2012; Salem et al. 2019). Balcik et al. (2010) reveal that disaster relief environments generally engage international non-governmental organisations (NGOs), host governments, the military, local and regional relief organisations and third party logistics service providers (3PLs), each having different interests, mandates, capacity and logistics expertise. Specifically, in such cases where there is high level of diversity amongst these organisations, intergroup leadership is often considered beneficial as it does not invoke identity crises among these organisations. Rather, it respects the identity of each organisation and welcomes diversity as an important characteristic for effectively managing disaster relief efforts. Following intergroup leadership theory (see, Hogg et al. 2012; Rast III et al. 2018), we argue that leaders cultivate unique and beneficial traits via team meetings, personal conversations or after-work occasions, which build special bonds amongst diverse groups engaged in disaster relief operations. These traits often help leaders to resolve conflicts that are a result of a lack of transparency. In this way, we view intergroup leadership as complementary to information alignment, collaboration and supply chain agility. Hence, we hypothesise the following as:

H5a: Intergroup leadership has positive and significant effect on the path joining information alignment and agility.

H5b: Intergroup leadership has positive and significant effect on the path joining collaboration and agility.

3. Research Design

We tested our hypotheses in the context of organisations involved in disaster relief humanitarian activities. We gathered our data from numerous and diverse participants (see Appendix A) drawn from various countries across Asia, Europe, Africa, North America, and South America (this is an extension of a previous study by Dubey et al. (2019a)). The collaboration amongst various humanitarian organisations focuses on partnerships. Hence, we used constructs to study the information alignment, collaboration among various humanitarian organisations and the agility in the supply chains. Following Ketokivi and Schroeder's (2004) guidelines, we used measures based on multiple respondents, who were expected to have in depth understanding about partnerships during disaster relief operations and supply chain agility.

Our target respondents were project directors, deputy directors, and managers from NGOs, UN specialized agencies, as well as service providers and contractors, as they are the people with direct responsibility for managing and monitoring disaster relief operations. We conducted our study with the help of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), who provided contact information of the international NGOs and the military forces involved in the disaster relief operations. We have completed several prior studies with the assistance of OCHA, which as an organisation offers different services that reduces the specific category effects (Moshtari, 2016; Dubey et al. 2019a, 2020a).

3.1 Survey Instrument Development

We adopted a two stage process of construct definition and identification of measurement items (Eckstein et al., 2015; Dubey et al. 2019a) (see Appendix B). Firstly, we undertook an extensive review of literature drawn from operations management and organisational studies' streams of management. Extant literature provided us with the construct's definitions and the initial list of items used for measuring each construct. Secondly, we adapted the constructs and their associated items to humanitarian settings (see, Moshtari et al., 2016; Dubey et al., 2019a; Dubey et al. 2020a). The items were measured on a five-point Likert scale, with anchors ranging from strongly disagree (1) to strongly agree (5). This scale assures high statistical variability amongst responses gathered using our structured survey-based instrument (see, Moshtari, 2016; Srinivasan and Swink, 2018; Dubey et al. 2019a; Salem et al. 2019; Dubey et al. 2020a) (see Appendix B).

We undertook two steps to pre-test our instrument, to ensure that respondents would not face any difficulties in understanding the items when completing the survey (Hensley, 1999; Boyer and Pagell, 2000). In the first step we invited five experienced researchers to complete the survey in order to elicit their critical opinion on the wording of the questions, specifically analysing them for ambiguity, clarity, and appropriateness of items (DeVellis, 1991). Following Dillman's (2011) suggestions, we further analysed the feedback of these researchers to understand whether our questions are appropriately set in the context of humanitarian settings. We then utilised all the opinions of the five researchers to modify the questions if necessary or to delete some questions which were deemed not relevant to the setting of disaster relief humanitarian activities (Chen and Paulraj, 2004). In the second step, we e-mailed our questionnaire to eight senior managers drawn from various NGOs who had extensive experience of managing complex disaster relief operations and who had in depth understanding of the subject matter. We requested these managers to provide their critical input on structure, readability, ambiguity, and completeness of the questions asked in the survey. Taking their feedback on board we finalised our survey instrument ready for data collection.

3.2 Data Collection

We started our data collection on 22nd February, 2019 and completed it on 23rd November, 2019. We collected data from various international NGOs, UN specialised agencies and service providers, as an extended part of a previous study (Dubey et al., 2019a). We sent our questionnaire via e-mail to nearly 1800 potential respondents from 600 organisations and followed-up with two e-mail reminders. We assured potential respondents that their information would remain anonymous and the data gathered would only be used for academic purposes. After careful examination of each response, we eliminated cases which failed to meet our selection criteria. This resulted in usable responses from 193 organisations (see Appendix A), an effective rate of 27.16%, with at least three participants from each individual organisation (a total of 613 multiple responses). Since we have gathered our data at one point of time, i.e. cross-sectional data using a survey based instrument, we needed to analyse if those respondents who did not return their survey may have affected our findings. This kind of bias is termed as non-response bias (Armstrong and Overton, 1977). To test for this bias we performed ANOVA analysis on our data split into two parts: early wave and late wave (see, wave analysis recommended by Armstrong and Overton, 1977). The test yielded no significant difference between

early-wave and late-wave groups of respondents ($p=0.32$). Hence, we conclude that non-response bias is not a concern in our study.

4. Data Analysis and Results

We have used PLS-SEM technique to test our theoretical model. Following Kock's (2019) arguments we have used Warp PLS 6.0 to address criticisms of traditional PLS-SEM methods due to them being composite-based, not factor-based. Recently, scholars have attempted to bridge the gap between factor-based and composite-based structural equation modelling (SEM) techniques (Kock, 2019). That is, in traditional PLS-SEM methods, latent variables are estimated as weighted aggregations of indicators without the inclusion of measurement errors (Henseler et al., 2014; Kock, 2019). Kock (2019) noted that traditional PLS-SEM ignore the measurement errors, which often leads to some known sources of bias; thus weakening the path coefficients with respect to their corresponding true values.

4.1 Multiple Rater Agreement Measures

As we have used multiple respondents in our study we need to assess the validity of the views of three or more respondents from one organisation. Following Ketokivi and Schroeder (2004) protocol we have performed inter-rater agreement analysis using four different methods: the percentage method (Boyer and Verma, 2000; Ketokivi and Schroeder, 2004), the ratio method (James et al., 1984; Boyer and Verma, 2000; Ketokivi and Schroeder, 2004), the inter-class correlation coefficient (Boyer and Verma, 2000) and paired t-test (Boyer and Verma, 2000; Ketokivi and Schroeder, 2004) (see, Appendix C). We therefore conclude, based on the results shown in Appendix C, that the inter-rater agreement in the data is acceptable.

4.2 Measurement Model Reliability and Validity

We adopted a two step process to validate our model (see Figure 1) as suggested in existing literature (see, Peng and Lai, 2012; Moshtari, 2016; Dubey et al. 2019a; Salem et al. 2019; Kock, 2019). Firstly, we examined the reliability and validity of our model with reflective constructs (Fornell and Larcker, 1981). Table 1 shows the result of confirmatory factor analysis (CFA) [i.e. the range of factor loadings (λ_i), the scale composite reliability (SCR), and average variance extracted (AVE)]. As shown in Table 1, factor loadings of each item are greater than 0.5 and significant at the 0.01 level, SCR of each

construct is greater than 0.7 and AVE of each construct is greater than 0.5, indicating sufficient convergent validity at indicator and construct levels (Fornell and Larcker, 1981).

Table 1: Measurement Properties of Constructs (Convergent Validity) (N=193)

Constructs	Items	Factor Loadings (λ_i)	Variance (λ_i^2)	Error ($1-\lambda_i^2$)	SCR	AVE
IA	IA1	0.66	0.43	0.57	0.83	0.56
	IA2	0.70	0.49	0.51		
	IA3	0.88	0.77	0.23		
	IA4	0.74	0.55	0.45		
CO	CO1	0.82	0.68	0.32	0.83	0.55
	CO2	0.69	0.47	0.53		
	CO3	0.74	0.55	0.45		
	CO4	0.71	0.50	0.50		
SCAG	SCAG1	0.74	0.55	0.45	0.78	0.54
	SCAG2	0.75	0.57	0.43		
	SCAG3	0.71	0.50	0.50		
AI-BDAC	AI-BDAC1	0.78	0.61	0.39	0.86	0.60
	AI-BDAC2	0.81	0.65	0.35		
	AI-BDAC3	0.81	0.65	0.35		
	AI-BDAC4	0.70	0.49	0.51		
IGL	IGL1	0.69	0.48	0.52	0.86	0.52
	IGL2	0.60	0.36	0.64		
	IGL3	0.73	0.53	0.47		
	IGL4	0.72	0.52	0.48		
	IGL5	0.77	0.59	0.41		
	IGL6	0.79	0.63	0.37		
I	I1	0.80	0.65	0.35	0.78	0.65
	I2	0.80	0.65	0.35		

Notes: IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; AI-BDAC, Artificial Intelligence driven big data analytics capability; IGL, Intergroup Leadership; I, Interdependency.

Secondly, we examined the divergent validity of measures used in our structural model (see Figure 1) via two methods: Fornell and Larcker’s criterion and HTMT (heterotrait-monotrait ratio of correlations). Following Fornell and Larcker (1981), we further examined the entries of the leading diagonal matrix (see Table 2), with the inter-correlation values in the given rows and columns. We observed that the square root values of each entries of leading diagonal, i.e. square root of AVE of construct, are greater than the inter-correlation values in each row and column in the matrix. Thus we conclude that our constructs possess sufficient divergent validity.

Table 2: Construct Correlations (Divergent Validity) (N=193)

	IA	CO	SCAG	AI-BDAC	IGL	I
IA	0.75					
CO	0.27	0.74				
SCAG	0.25	0.37	0.73			
AI-BDAC	-0.01	0.09	0.05	0.77		
IGL	0.26	0.23	0.21	0.15	0.72	
I	0.02	-0.02	-0.04	-0.07	0.01	0.81

Notes: IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; AI-BDAC, Artificial Intelligence driven big data analytics capability; IGL, Intergroup Leadership; I, Interdependency.

In addition, we assessed the discriminant validity among constructs via HTMT criterion test. The HTMT values (see, Table 3) between reflective constructs are below 0.90, suggesting that adequate discriminant validity exist for all the constructs (Henseler et al. 2015).

Table 3: HTMT Values

	IA	CO	SCAG	AI-BDAC	IGL	I
IA						
CO	0.364					
SCAG	0.263	0.376				
AI-BDAC	0.157	0.162	0.211			
IGL	0.286	0.749	0.843	0.186		
I	0.223	0.617	0.667	0.114	0.812	

Notes: IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; AI-BDAC, Artificial Intelligence driven big data analytics capability; IGL, Intergroup Leadership; I, Interdependency.

4.3 Common Method Bias (CMB)

As we use a survey based instrument to collect data there is a possibility that common method bias (CMB) may contaminate our results (Podsakoff and Organ, 1986; Podsakoff et al., 2003). Whilst we do not claim to have completely eliminated the chance of CMB occurring, following the suggestions of Ketokivi and Schroeder (2004) we aim to reduce its effects by using multi-informant data. Further, we have examined CMB in multiple ways. Firstly, we performed traditional one factor Harman’s test (single factor explained nearly 21.21% of the total variance). Secondly, we examined for CMB via correlation marker technique (Lindell and Whitney, 2001). We adopted an unrelated variable to partial out correlations caused by CMB. Additionally, we determined the significant values of correlations, as suggested by Lindell and Whitney (2001). We noted minimal differences between the adjusted and unadjusted correlations. Therefore, based on these statistical results, we conclude that CMB is not a major issue in our study.

Following Kock’s (2017) recommendations, we also calculated nonlinear bivariate causality direction ratio (NLBCDR). The NLBCDR measures the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in the proposed theoretical model (Kock, 2012, p.52-53). The acceptable value should be ≥ 0.7 . In our study we found NLBCDR=0.88 (approx.), which is greater than the critical value of 0.7. We therefore conclude that causality is not a major issue. We have further provided the values for model fit and quality indices supporting this conclusion in Appendix D.

4.4 Hypotheses Testing

Table 4 provides the results of PLS-SEM analysis. The hypotheses H1-H3 examine the linkage between information alignment, collaboration and supply chain agility. Firstly, we found support for H1 (IA→CO) ($\beta=0.28$; $p<0.001$). This finding is consistent with previous literature (see, Chi et al. 2020). Next, we found support for H2 (IA→SCAG) ($\beta=0.38$; $p<0.001$). This findings is also consistent with our previous studies (Tallon and Pinsonneault, 2011; Fawcett and Fawcett, 2013). Addressing, H3 (CO→SCAG), we found support ($\beta=0.75$; $p<0.001$), which is consistent with previous arguments (see, Lee, 2004).

We have further tested the interaction effects of AI-BDAC and intergroup leadership on the paths joining IA/CO and SCAG (H4a/b & H5a/b). We found support for H4a ($\beta=0.38$; $p<0.001$) and H4b ($\beta=0.33$; $p<0.001$). Similarly, we found support for H5a ($\beta=0.27$; $p<0.001$) and H5b ($\beta=0.36$; $p<0.001$). Our findings paint an interesting picture. Our findings further extend the Salem et al. (2019) findings by examining the moderating influence of intergroup leadership. However, we did not find support for control variables interdependency (I) ($\beta=0.002$; $p>0.1$) and relationship duration (RD) ($\beta=-0.010$; $p>0.1$). We interpret these observations as demonstrating that the interdependency (i.e. the degree to which partners are dependent on each other) and relationship duration (i.e. the age of collaborative relationship between disaster relief groups) does not produce significant effects on supply chain agility.

Table 4: Structural Estimates (N=193)

<i>Hypothesis</i>	<i>Effect of</i>	<i>Effect on</i>	β	<i>p-value</i>	<i>Results</i>
H1	IA	CO	0.28	<0.001	supported
H2	IA	SCAG	0.38	<0.001	supported
H3	CO	SCAG	0.75	<0.001	supported
Interaction effects					
H4a	IA*AI-BDAC		0.38	<0.001	supported
H4b	CO*AI-BDAC		0.33	<0.001	supported
H5a	IA*IGL		0.27	<0.001	supported
H5b	CO*IGL		0.36	<0.001	supported
<i>Control variables</i>					

	I	SCAG	0.02	>0.1	Not-supported
	RD	SCAG	-0.010	>0.1	Not-supported

To further examine the explanatory power of our theoretical model (see Figure 1) we analysed the explanatory power (R^2) of the endogenous constructs as shown in Appendix E. The IA explains nearly 32% of the total variance in CO ($R^2=0.32$) and the IA and CO explain nearly 83% of the total variance of SCAG (see Figure 2). We further determined the effect size (f^2) value of CO using Cohen's f^2 formula. Consequently, the effect size of IA on CO is 0.21 and on SCAG is 0.27 and CO on SCAG is 0.72. We additionally examined the predictability of the model. Stone-Geiser's Q^2 values of endogenous constructs are CO (0.18) and SCAG (0.88) (see Appendix E), which are greater than zero. With these results, we find that the AI-BDAC has significant predictive capability (Peng and Lai, 2012). Figure 2 shows the validated conceptual framework after SEM analysis.

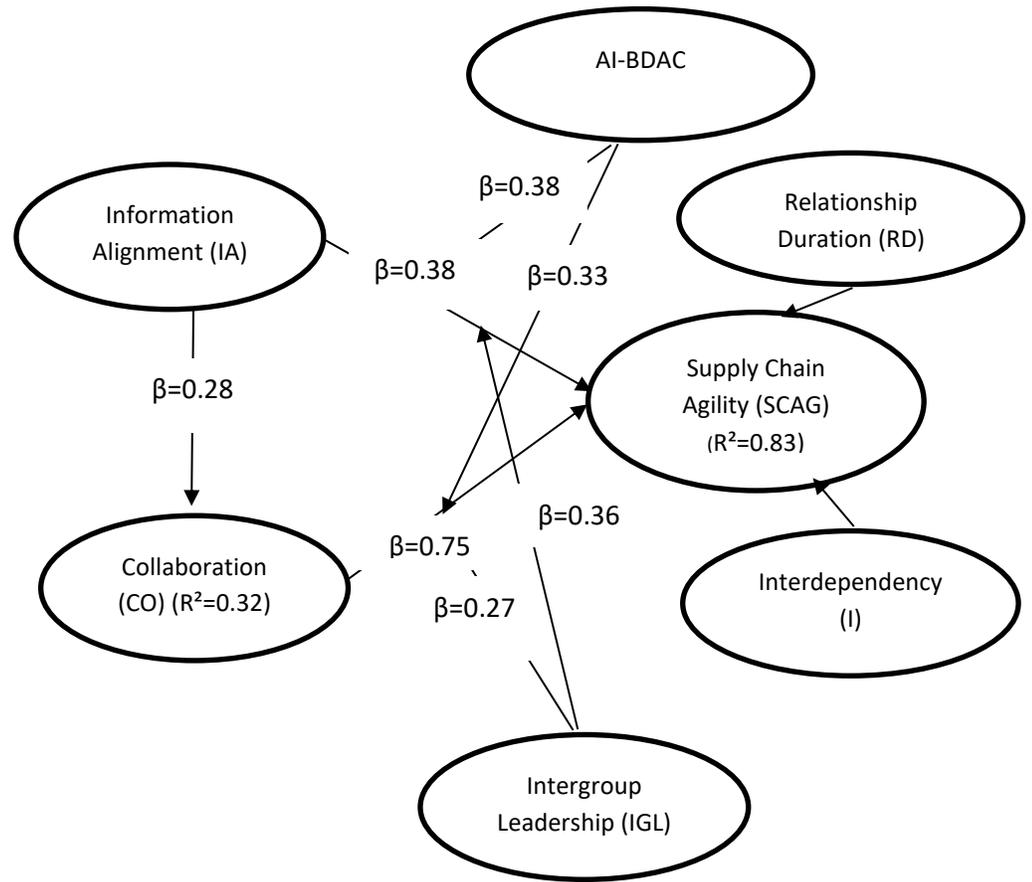


Figure 2: Final Model

5. Discussion

Our results paint an interesting picture of associations amongst information alignment, collaboration and supply chain agility from resources and capability perspective. They reveal how agility in humanitarian supply chains is enhanced within collaborative relationships developed via artificial intelligence driven big data analytics capability and intergroup leadership. The results, derived via statistical analysis, use empirical data gathered from a pretested instrument. They highlight how the interplay between tangible and intangible resources further help to enhance collaboration amongst the disaster relief operations partners and supply chain agility. Furthermore, the moderating effects of AI-BDAC and IGL on the paths joining IA/CO and SCAG provide nuanced understanding of how artificial intelligence driven big data analytics capability and intergroup leadership influences the supply

chain agility in humanitarian supply chains. Collectively, these findings offer some useful contributions to theory and some interesting directions for the managers engaged in disaster relief operations. Furthermore, the findings raise potential research questions that help to advance future research.

5.1 Implications for Theory

Our study offers some important contributions to existing theoretical debates. Firstly, we demonstrate that IA and CO, as two distinct types of resources, in combination can help to generate SCAG. Prior to our study, the extant literature has not offered any clarity on the possible link between IA, CO and SCAG. Previous studies, i.e. Tan et al. (2010) and Ng et al. (2013), have argued to recognise the importance of information alignment in building partnerships. However, these studies were conducted in the context of commercial enterprises and, to date, humanitarian scholars have remained silent in terms of the interplay of resources and capabilities in generating competitive advantage.

Secondly, our study provides empirical evidence that information alignment and collaboration act as antecedents to agility in humanitarian supply chains (see Figure 2). This is one of the few studies utilising a survey based approach to test such hypothesised relationships. The existing literature has offered anecdotal evidence, with little theory driven and empirically tested results. Existing literature has often studied the interplay of resources and capabilities to examine the level of agility (Swafford et al. 2006; Braunscheidel and Suresh, 2009; Blome et al. 2013; Dubey et al. 2019d; Gligor et al. 2015). However, in the context of humanitarian operations, theory driven research, using empirical data, is scant. Hence, our study attempts to disentangle the concept of agility from its predominant commercial organisations' perspective. Although we have taken our arguments from commercial supply chain literature and organisational studies, the pretesting exercise in the context to humanitarian settings offers different and interesting perspectives.

Thirdly, building upon previous findings (see, Salem et al. 2019), we have examined the moderating role of intergroup leadership. The operations management literature has acknowledged the role of top management commitment and leadership (see, de Koster et al. 2011; Lee et al. 2011; Dubey et al. 2018), in enhancing performance. However, based on Hogg et al.'s (2012) arguments, we posit that humanitarian operations are complex in terms of the nature and characteristics of the hastily formed teams. Salem et al. (2019) have examined the relationship between intergroup leadership and humanitarian operations performance under the mediating effect of cooperation. We have further extended the arguments via testing the moderating effect of IGL on the paths joining IA/CO and

SCAG. We believe, our results paint an interesting picture about intergroup leadership theory, which may help to explain the complex interaction between technology and humanitarian groups.

Despite some interesting contributions, we believe that there is still sufficient room for further investigations. For instance, we are yet to understand how intergroup leadership may help to address the dilemma of managing the interplay between inter-organisational cultural complexities, inter-organisational learning and intergroup leadership in the context of humanitarian settings; where the COVID-19 pandemic has exposed limitations of our management of disaster relief operations. Moreover, despite the great number of emerging technologies, most of the disaster relief efforts has failed to address complexities associated with the human and technology interface. In understanding and then addressing these complexities in humanitarian settings there is an urgent need for theory driven and data driven studies.

5.2 Implications for Practice

This study offers a number of useful implications for managers engaged in managing disaster relief operations. In the past, we have witnessed significant investment in building advance technological capabilities. However, investment in these technologies alone cannot help organisations – including those involved in humanitarian endeavours – achieve the desired levels of success. Alongside utilising the right technologies, there need to be leaders with the right traits to direct the complex activities that take place in disaster relief. Our findings, which are based on arguments drawn from extant literature and data gathered using a pre-tested instrument, confirm that intergroup leadership, with the associated required traits, may play a significant role in the effective working of hastily formed organisations, as is the case for disaster relief. Previous work by Schiffing et al. (2020a) has shown how crucial personal connections are for enabling swift actions in humanitarian responses. We provide evidence for the influence of intergroup leadership in particular on supply chain agility, which is a desirable trait in many humanitarian supply chains. In addition, information alignment and collaboration can together play a significant role in explaining the presence of agility in humanitarian supply chains. Hence, managers need to understand the interplay of, and maintain a fine balance between, information alignment and collaboration, while also focusing on leadership that enables intergroup connections. This should inform training of humanitarian supply chain professionals and leaders. Furthermore, the balance between information alignment and collaboration should be an

important consideration in designing and operationalising interactions between different humanitarian organisations if supply chain agility is of importance,

Finally, our results offer useful observations in relation to relationship duration and interdependency of the parties that make up humanitarian supply chains. In the past, literature has highlighted the role of relationship duration and interdependency in building agility in different organisational contexts. However, our results suggest that for managers of humanitarian efforts such a role might be difficult to establish, as we found no significant relationship between relationship duration, interdependency and agility. This may be attributable to the specific characteristics of the humanitarian organisations, such as there is very little time to build relationships, so duration is not a critical variable and swift trust is vital to many interactions. For managers, this can be an encouraging finding as agility has not been shown to depend on long-term relationships, which may often be unattainable in disaster relief contexts. Although, in respect of this observation, we caution our readers that our results must be interpreted with respect to this particular situation and the findings need further testing in different contexts; thus there is a need for careful interpretation. That said, it is clear that managers who seek greater agility in the responses of their supply chain partners, may need to look for other antecedents, besides relationship durations and interdependency, and uncovering these antecedents is a potentially fruitful avenue for future research.

5.3 Limitations and Further Research Directions

Humanitarian organisations and other aid agencies recognise the benefits of using emerging technologies to improve information alignment and collaboration. Furthermore, donors are increasingly demanding more transparency, becoming less tolerant of the inefficiencies arising during disaster relief operations, and, therefore, demanding more collaborative efforts among humanitarian organisations (Moshtari, 2016). Our study contributes to the technology-enabled collaboration, intergroup leadership and supply chain agility literature, specifically in the context of humanitarian supply chains. However, despite our efforts via using established organisational theories, as well as testing our research hypotheses using multi-informant data gathered using a pre-tested questionnaire with the help of reputable organisations, we feel that our study has some limitations.

Firstly, we have focused on the application of a few antecedents, information alignment and collaboration, to empirically investigate the interplay of these two resources and capabilities in enhancing agility in humanitarian supply chains. Hence, future studies can explore how other

organisational factors may enhance agility in the technology era, including how factors might interact in negative ways, such as the misuse of technology providing an inhibitor to the interplay of IA and CO. Additionally, our current study has not considered other potentially significant variables, such as organisational culture or the attitude of those involved in humanitarian activities towards the usage of technologies.

Secondly, disparities of power amongst partners may yield different outcomes. Although, we have partially recognised the potential influence of disparity in power structures and their effects on collaboration by introducing the concept of intergroup leadership to iron out such differences, still our understanding of the interplay of intergroup leadership in complex humanitarian context remains limited. Although Salem et al. (2019) offers a comprehensive perspective, still lot of questions relating to intergroup leadership in the context to humanitarian settings need answering.

Finally, we have utilised cross-sectional survey data to test our research hypotheses. Hence, with the help of cross-sectional data, the cause and effects relationship between constructs may not be understood. Thus, to address such limitations, we recommend further research involving the collection of panel data. However, we recognise the challenges in obtaining such panel data in humanitarian settings and hence a possible solution could be the collection of multi-level data (see, Dubey et al. 2019a).

6. Conclusions

Our study examined the interplay between information alignment and collaboration in order to improve supply chain agility in the context of humanitarian settings. To further substantiate our arguments, we introduced the moderating role of AI-BDAC and intergroup leadership to explain how emerging technology and different traits of leadership help complex humanitarian organisations to achieve significant results. We have grounded our arguments in established resource based view (RBV) and contingency theory, as we have recognised the need for such theories to explain the differential effects of emerging technologies and intergroup leadership on agility in humanitarian settings. To test our research hypotheses we used multi-informant survey data, as suggested by Ketokivi and Schroeder (2004). In this way, we have tried to address previous concerns raised by a majority of the operations and supply chain management scholars. Our results offer some useful insights to future scholars and managers. Further, we have noted some limitations of our study that may help shape future research agendas and, thus, we hope that our study may offer enough ingredients for further research that will

in turn add to the ongoing debate. Finally, we hope our study provides insight into understanding the relationships between critical elements of humanitarian supply chains, which may be utilised to better manage the disaster relief efforts.

References

- Akhtar, P., Marr, N. E., & Garnevskaja, E. V. (2012). Coordination in humanitarian relief chains: chain coordinators. *Journal of Humanitarian Logistics and Supply Chain Management*, 2(1), 85-103.
- Akhtar, P., Khan, Z., Rao-Nicholson, R., & Zhang, M. (2019). Building relationship innovation in global collaborative partnerships: big data analytics and traditional organizational powers. *R&D Management*, 49(1), 7-20.
- Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics*, 182, 113-131.
- Akter, S., & Wamba, S. F. (2019). Big data and disaster management: a systematic review and agenda for future research. *Annals of Operations Research*, 283(1-2), 939-959.
- Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2020). Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*, 1-33. DOI: 10.1007/s10479-020-03620-w.
- Altay, N., & Pal, R. (2014). Information Diffusion among Agents: Implications for Humanitarian Operations. *Production and Operations Management*, 23(6), 1015-1027.
- Altay, N., Gunasekaran, A., Dubey, R., & Childe, S. J. (2018). Agility and resilience as antecedents of supply chain performance under moderating effects of organizational culture within the humanitarian setting: a dynamic capability view. *Production Planning & Control*, 29(14), 1158-1174.
- Altay, N., & Labonte, M. (2014). Challenges in humanitarian information management and exchange: evidence from Haiti. *Disasters*, 38(s1), S50-S72.
- Alvesson, M., & Sandberg, J. (2011). Generating research questions through problematization. *Academy of Management Review*, 36(2), 247-271.
- Aragón-Correa, J. A., & Sharma, S. (2003). A contingent resource-based view of proactive corporate environmental strategy. *Academy of Management Review*, 28(1), 71-88.
- Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3), 396-402.

- Balcik, B., Beamon, B. M., Krejci, C. C., Muramatsu, K. M., & Ramirez, M. (2010). Coordination in humanitarian relief chains: practices, challenges and opportunities. *International Journal of Production Economics*, 126(1), 22-34.
- Barratt, M. (2004). Understanding the meaning of collaboration in the supply chain. *Supply Chain Management: an international journal*, 9(1), 30-42.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Blome, C., Schoenherr, T., & Rexhausen, D. (2013). Antecedents and enablers of supply chain agility and its effect on performance: a dynamic capabilities perspective. *International Journal of Production Research*, 51(4), 1295-1318.
- Boyd, B. K., Takacs Haynes, K., Hitt, M. A., Bergh, D. D., & Ketchen Jr, D. J. (2012). Contingency hypotheses in strategic management research: Use, disuse, or misuse?. *Journal of Management*, 38(1), 278-313.
- Boyer, K. K., & Pagell, M. (2000). Measurement issues in empirical research: improving measures of operations strategy and advanced manufacturing technology. *Journal of Operations Management*, 18(3), 361-374.
- Boyer, K. K., & Verma, R. (2000). Multiple raters in survey-based operations management research: a review and tutorial. *Production and Operations Management*, 9(2), 128-140.
- Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, 50(3), 55-73.
- Braunscheidel, M. J., & Suresh, N. C. (2009). The organizational antecedents of a firm's supply chain agility for risk mitigation and response. *Journal of Operations Management*, 27(2), 119-140.
- Caldwell, B. S., Palmer III, R. C., & Cuevas, H. M. (2008). Information alignment and task coordination in organizations: An 'information clutch' metaphor. *Information Systems Management*, 25(1), 33-44.
- Chan, Y. E., & Reich, B. H. (2007). IT alignment: what have we learned?. *Journal of Information Technology*, 22(4), 297-315.
- Charles, A., Luras, M., & Van Wassenhove, L. (2010). A model to define and assess the agility of supply chains: building on humanitarian experience. *International Journal of Physical Distribution & Logistics Management*, 40(8/9), 722-741.

- Chen, I. J., & Paulraj, A. (2004). Towards a theory of supply chain management: the constructs and measurements. *Journal of Operations Management*, 22(2), 119-150.
- Chen, J., Sohal, A. S., & Prajogo, D. I. (2013). Supply chain operational risk mitigation: a collaborative approach. *International Journal of Production Research*, 51(7), 2186-2199.
- Chen, H. Y., Das, A., & Ivanov, D. (2019). Building resilience and managing post-disruption supply chain recovery: Lessons from the information and communication technology industry. *International Journal of Information Management*, 49, 330-342.
- Chi, M., Huang, R., & George, J. F. (2020). Collaboration in demand-driven supply chain: Based on a perspective of governance and IT-business strategic alignment. *International Journal of Information Management*, 52, 102062.
- Chopra, S., & Sodhi, M. S. (2004). Supply-chain breakdown. *MIT Sloan Management Review*, 46(1), 53-61.
- Clarke, P. K., & Campbell, L. (2018). Coordination in theory, coordination in practice: the case of the Clusters. *Disasters*, 42(4), 655-673.
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale, NJ: L. Erlbaum Associates.
- Day, J. M., Melnyk, S. A., Larson, P. D., Davis, E. W., & Whybark, D. C. (2012). Humanitarian and disaster relief supply chains: A matter of life and death. *Journal of Supply Chain Management*, 48(2), 21-36.
- de Koster, R. B., Stam, D., & Balk, B. M. (2011). Accidents happen: The influence of safety-specific transformational leadership, safety consciousness, and hazard reducing systems on warehouse accidents. *Journal of Operations Management*, 29(7-8), 753-765.
- DeVellis, R. F. (1991). Guidelines in scale development. *Scale Development: Theory and Applications*. Newbury Park, Calif: Sage, 5191.
- Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F. R., Gaughan, A. E., ... & Tatem, A. J. (2014). Dynamic population mapping using mobile phone data. *Proceedings of the National Academy of Sciences*, 111(45), 15888-15893.
- Dillman, D. A. (2011). *Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide*. John Wiley & Sons.
- Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, 56(1-2), 414-430.

- Dolgui, A., Ivanov, D., Potryasaev, S., Sokolov, B., Ivanova, M., & Werner, F. (2020a). Blockchain-oriented dynamic modelling of smart contract design and execution in the supply chain. *International Journal of Production Research*, 58(7), 2184-2199.
- Dolgui, A., Ivanov, D., & Sokolov, B. (2020b). Reconfigurable supply chain: the X-network. *International Journal of Production Research*, 1-26. DOI: 10.1080/00207543.2020.1774679.
- Donaldson, L. (2001). *The contingency theory of organizations*. Sage.
- Dubey, R., Singh, T., & Gupta, O. K. (2015). Impact of agility, adaptability and alignment on humanitarian logistics performance: mediating effect of leadership. *Global Business Review*, 16(5), 812-831.
- Dubey, R., Altay, N., Gunasekaran, A., Blome, C., Papadopoulos, T., & Childe, S. J. (2018). Supply chain agility, adaptability and alignment. *International Journal of Operations & Production Management*, 38(1), 129-148.
- Dubey, R., Gunasekaran, A., Childe, S. J., Roubaud, D., Wamba, S. F., Giannakis, M., & Foropon, C. (2019a). Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *International Journal of Production Economics*, 210, 120-136.
- Dubey, R., Altay, N., & Blome, C. (2019b). Swift trust and commitment: The missing links for humanitarian supply chain coordination? *Annals of Operations Research*, 283(1), 159-177.
- Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., & Papadopoulos, T. (2020a). Blockchain technology for enhancing swift-trust, collaboration and resilience within a humanitarian supply chain setting. *International Journal of Production Research*, 58(11), 3381-3398.
- Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., & Hazen, B. T. (2020b). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, 107599.
- Duong, L. N. K., & Chong, J. (2020). Supply chain collaboration in the presence of disruptions: a literature review. *International Journal of Production Research*, 58(11), 3488-3507.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Galanos, V. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 101994, doi: <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>

- Dwivedi, Y. K., Shareef, M. A., Mukerji, B., Rana, N. P., & Kapoor, K. K. (2018). Involvement in emergency supply chain for disaster management: a cognitive dissonance perspective. *International Journal of Production Research*, 56(21), 6758-6773.
- Eckstein, D., Goellner, M., Blome, C., & Henke, M. (2015). The performance impact of supply chain agility and supply chain adaptability: the moderating effect of product complexity. *International Journal of Production Research*, 53(10), 3028-3046.
- Fan, C., Zhang, C., Yahja, A., & Mostafavi, A. (2019). Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *International Journal of Information Management*, 102049, doi: <https://doi.org/10.1016/j.ijinfomgt.2019.102049>
- Fawcett, A. M., & Fawcett, S. E. (2013). Benchmarking the state of humanitarian aid and disaster relief. *Benchmarking: An International Journal*, 20(5), 661-692.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- Fosso Wamba, S., Edwards, A., & Akter, S. (2019). Social media adoption and use for improved emergency services operations: the case of the NSW SES. *Annals of Operations Research*, 283(1-2), 225-245.
- Fosso Wamba, S., & Queiroz, M. M. (2020). Blockchain in the operations and supply chain management: Benefits, challenges and future research opportunities. *International Journal of Information Management*, 52, 102064.
- Fosso Wamba, S., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, 222, 107498.
- Fragapane, G., Ivanov, D., Peron, M., Sgarbossa, F., & Strandhagen, J. O. (2020). Increasing flexibility and productivity in industry 4.0 production networks with autonomous mobile robots and smart intralogistics. *Annals of operations research*, 1-19. DOI: 10.1007/s10479-020-03526-7
- Gligor, D. M., Esmark, C. L., & Holcomb, M. C. (2015). Performance outcomes of supply chain agility: when should you be agile?. *Journal of Operations Management*, 33, 71-82.
- Gooty, J., Connelly, S., Griffith, J., & Gupta, A. (2010). Leadership, affect and emotions: A state of the science review. *The Leadership Quarterly*, 21(6), 979-1004.
- Grant, R. M. (1991). The resource-based theory of competitive advantage: implications for strategy formulation. *California Management Review*, 33(3), 114-135.

- Größler, A., & Grübner, A. (2006). An empirical model of the relationships between manufacturing capabilities. *International Journal of Operations & Production Management*, 26(5), 458-485.
- Guide Jr, V. D. R., & Ketokivi, M. (2015). Notes from the Editors: Redefining some methodological criteria for the journal★. *Journal of Operations Management*, 37(1), v-viii.
- Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, 70, 308-317.
- Gunasekaran, A., Dubey, R., Fosso Wamba, S., Papadopoulos, T., Hazen, B. T., & Ngai, E. W. (2018). Bridging humanitarian operations management and organisational theory, *International Journal of Production Research*, 56(21), 6735-6740.
- Gupta, S., Altay, N., & Luo, Z. (2019). Big data in humanitarian supply chain management: a review and further research directions. *Annals of Operations Research*, 283(1), 1153-1173.
- Hair, J., Black, W., Babin, B., & Anderson, R. (2009). *Multivariate Data Analysis*, London: Prentice Hall.
- Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., ... & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, 17(2), 182-209.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115-135.
- Hensley, R. L. (1999). A review of operations management studies using scale development techniques. *Journal of Operations Management*, 17(3), 343-358.
- Hitt, M. A., Ireland, R. D., Sirmon, D. G., & Trahms, C. A. (2011). Strategic entrepreneurship: creating value for individuals, organizations, and society. *Academy of Management Perspectives*, 25(2), 57-75.
- Hitt, M. A., Carnes, C. M., & Xu, K. (2016). A current view of resource based theory in operations management: A response to Bromiley and Rau. *Journal of Operations Management*, 41(10), 107-109.
- Hogg, M. A., Van Knippenberg, D., & Rast III, D. E. (2012). Intergroup leadership in organizations: Leading across group and organizational boundaries. *Academy of Management Review*, 37(2), 232-255.
- Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829-846.

- Ivanov, D. (2020a). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136, 101922.
- Ivanov D. (2020b). Viable Supply Chain Model: Integrating agility, resilience and sustainability perspectives – lessons from and thinking beyond the COVID-19 pandemic. *Annals of Operations Research*, DOI: 10.1007/s10479-020-03640-6.
- Ivanov, D., & Dolgui, A. (2020a). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research*, 58(10), 2904-2915.
- Ivanov, D., & Dolgui, A. (2020b). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 1-14. DOI: 10.1080/09537287.2020.1768450
- Ivanov, D., Tang, C. S., Dolgui, A., Battini, D., & Das, A. (2020). Researchers' perspectives on Industry 4.0: multi-disciplinary analysis and opportunities for operations management. *International Journal of Production Research*, 1-24. DOI: 10.1080/00207543.2020.1798035.
- Jahre, M., & Jensen, L. M. (2010). Coordination in humanitarian logistics through clusters. *International Journal of Physical Distribution & Logistics Management*, 40(8/9), 657-674.
- Jain, V., Benyoucef, L., & Deshmukh, S. G. (2008). A new approach for evaluating agility in supply chains using fuzzy association rules mining. *Engineering Applications of Artificial Intelligence*, 21(3), 367-385.
- Kabra, G., & Ramesh, A. (2015). Analyzing drivers and barriers of coordination in humanitarian supply chain management under fuzzy environment. *Benchmarking: An International Journal*, 22(4), 559-587.
- Kearns, G. S., & Lederer, A. L. (2003). A resource-based view of strategic IT alignment: how knowledge sharing creates competitive advantage. *Decision Sciences*, 34(1), 1-29.
- Kent, R. C. (2004). The United Nations' humanitarian pillar: Refocusing the UN's disaster and emergency roles and responsibilities. *Disasters*, 28(2), 216-233.
- Ketchen Jr, D. J., & Hult, G. T. M. (2007). Bridging organization theory and supply chain management: The case of best value supply chains. *Journal of Operations Management*, 25(2), 573-580.
- Kim, S. S., & Malhotra, N. K. (2005). A longitudinal model of continued IS use: An integrative view of four mechanisms underlying post adoption phenomena. *Management Science*, 51(5), 741-755.
- Kock, N. (2012). WarpPLS 5.0 user manual. Laredo, TX: ScriptWarp Systems.

- Kock, N. (2017). Common method bias: A full collinearity assessment method for PLS-SEM. In *Partial least squares path modeling* (pp. 245-257). Springer, Cham.
- Kock, N. (2019). From composites to factors: Bridging the gap between PLS and covariance-based structural equation modelling. *Information Systems Journal*, 29(3), 674-706.
- Laaksonen, T., Jarimo, T., & Kulmala, H. I. (2009). Cooperative strategies in customer–supplier relationships: The role of interfirm trust. *International Journal of Production Economics*, 120(1), 79-87.
- Larson, P. D., & Foropon, C. (2018). Process improvement in humanitarian operations: an organisational theory perspective. *International Journal of Production Research*, 56(21), 6828-6841.
- Lawrence, P. & Lorsch, J. (1967). *Organization and Environment: Managing Differentiation and Integration*. Boston, MA: Division of Research, Graduate School of Business Administration, Harvard University.
- Lee, H. L. (2004). The triple-A supply chain. *Harvard Business Review*, 82(10), 102-113.
- Li, Q., Wang, C., Wu, J., Li, J., & Wang, Z. Y. (2011). Towards the business–information technology alignment in cloud computing environment: an approach based on collaboration points and agents. *International Journal of Computer Integrated Manufacturing*, 24(11), 1038-1057.
- L'Hermitte, C., Tatham, P., Bowles, M., & Brooks, B. (2016). Developing organisational capabilities to support agility in humanitarian logistics. *Journal of Humanitarian Logistics and Supply Chain Management*, 6(1), 72-99.
- Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, 86(1), 114-121.
- Ling-Yee, L. (2007). Marketing resources and performance of exhibitor firms in trade shows: A contingent resource perspective. *Industrial Marketing Management*, 36(3), 360-370.
- Madhok, A. (2002). Reassessing the fundamentals and beyond: Ronald Coase, the transaction cost and resource-based theories of the firm and the institutional structure of production. *Strategic Management Journal*, 23(6), 535-550.
- Makadok, R. (1998). Can first-mover and early-mover advantages be sustained in an industry with low barriers to entry/imitation?. *Strategic Management Journal*, 19(7), 683-696.
- McLachlin, R., & Larson, P. D. (2011). Building humanitarian supply chain relationships: lessons from leading practitioners. *Journal of Humanitarian Logistics and Supply Chain Management*, 1(1), 32-49.
- Moshtari, M. (2016). Inter-organizational fit, relationship management capability, and collaborative performance within a humanitarian setting. *Production and Operations Management*, 25(9), 1542-1557.

- Newbert, S. L. (2007). Empirical research on the resource-based view of the firm: an assessment and suggestions for future research. *Strategic Management Journal*, 28(2), 121-146.
- Ng, I. C., Ding, D. X., & Yip, N. (2013). Outcome-based contracts as new business model: The role of partnership and value-driven relational assets. *Industrial Marketing Management*, 42(5), 730-743.
- Nurmala, N., de Vries, J., & de Leeuw, S. (2018). Cross-sector humanitarian–business partnerships in managing humanitarian logistics: an empirical verification. *International Journal of Production Research*, 56(21), 6842-6858.
- Oliver, C. (1997). Sustainable competitive advantage: combining institutional and resource-based views. *Strategic Management Journal*, 18(9), 697-713.
- Pedraza-Martinez, A. J., Stapleton, O., & Van Wassenhove, L. N. (2013). On the use of evidence in humanitarian logistics research. *Disasters*, 37(s1), S51-S67.
- Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management*, 30(6), 467-480.
- Peretti, U., Sgarbossa, F., Battini, D., & Persona, A. (2014). Application of humanitarian last mile distribution model. *Journal of Humanitarian Logistics and Supply Chain Management*, 4(1), 131-148.
- Pettit, S., & Beresford, A. (2009). Critical success factors in the context of humanitarian aid supply chains. *International Journal of Physical Distribution & Logistics Management*, 39(6), 450-468.
- Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, 12(4), 531-544.
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.
- Poom, A., Järvi, O., Zook, M., & Toivonen, T. (2020). COVID-19 is spatial: Ensuring that mobile Big Data is used for social good. *Big Data & Society*, 7(2), 2053951720952088.
- Prakash, C., Besiou, M., Charan, P., & Gupta, S. (2020). Organization theory in humanitarian operations: a review and suggested research agenda. *Journal of Humanitarian Logistics and Supply Chain Management*, 10(2), 261-284.
- Prasad, S., Woldt, J., Tata, J., & Altay, N. (2019). Application of project management to disaster resilience. *Annals of Operations Research*, 283(1-2), 561-590.
- Prasanna, S. R., & Haavisto, I. (2018). Collaboration in humanitarian supply chains: an organisational culture framework. *International Journal of Production Research*, 56(17), 5611-5625.

- Premkumar, G., & King, W. R. (1994). Organizational characteristics and information systems planning: An empirical study. *Information Systems Research*, 5(2), 75-109.
- Podsakoff, P. M., MacKenzie, S. B., Podsakoff, N. P., & Lee, J. Y. (2003). The mismeasure of man (agement) and its implications for leadership research. *The Leadership Quarterly*, 14(6), 615-656.
- Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, 12(4), 531-544.
- Qi, Y., Huo, B., Wang, Z., & Yeung, H. Y. J. (2017). The impact of operations and supply chain strategies on integration and performance. *International Journal of Production Economics*, 185, 162-174.
- Queiroz, M. M., & Telles, R. (2018). Big data analytics in supply chain and logistics: An empirical approach. *The International Journal of Logistics Management*, 29(2), 767-783.
- Queiroz M., Ivanov D., Dolgui A., Fosso Wamba, S. (2020). Impacts of Epidemic Outbreaks on Supply Chains: Mapping a Research Agenda Amid the COVID-19 Pandemic through a Structured Literature Review. *Annals of Operations Research*, DOI: 10.1007/s10479-020-03685-7.
- Ragini, J. R., Anand, P. R., & Bhaskar, V. (2018). Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management*, 42, 13-24.
- Rast III, D. E., Hogg, M. A., & van Knippenberg, D. (2018). Intergroup leadership across distinct subgroups and identities. *Personality and Social Psychology Bulletin*, 44(7), 1090-1103.
- Ravichandran, T., Lertwongsatien, C., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of Management Information Systems*, 21(4), 237-276.
- Reich, B. H., & Benbasat, I. (2000). Factors that influence the social dimension of alignment between business and information technology objectives. *MIS Quarterly*, 24(1), 81-113.
- Rodríguez-Espíndola, O., Chowdhury, S., Beltagui, A., & Albores, P. (2020). The potential of emergent disruptive technologies for humanitarian supply chains: the integration of blockchain, Artificial Intelligence and 3D printing. *International Journal of Production Research*, 1-21. DOI: 10.1080/00207543.2020.1761565.
- Rosenthal, R., & Rosnow, R. L. (1991). *Essentials of behavioral research: Methods and data analysis*. McGraw-Hill Humanities Social.
- Rumelt, R. P. (1984). Towards a strategic theory of the firm. *Competitive Strategic Management*, 26(3), 556-570.

- Salem, M., Van Quaquebeke, N., Besiou, M., & Meyer, L. (2019). Intergroup Leadership: How Leaders Can Enhance Performance of Humanitarian Operations. *Production and Operations Management*, 28(11), 2877-2897.
- Schiffeling, S., Hannibal, C., Fan, Y. and Tickle, M. (2020a). Coopetition in temporary contexts: examining swift trust and swift distrust in humanitarian operations. *International Journal of Operations & Production Management*. Ahead-of-print.
- Schiffeling, S., Hannibal, C., Tickle, M. and Fan, Y. (2020b). The implications of complexity for humanitarian logistics: a complex adaptive systems perspective. *Annals of Operations Research*. Ahead-of-print.
- Sharma, S. K., Misra, S. K., & Singh, J. B. (2020). The role of GIS-enabled mobile applications in disaster management: A case analysis of cyclone Gaja in India. *International Journal of Information Management*, 51, 102030.
- Simatupang, T. M., & Sridharan, R. (2005). The collaboration index: a measure for supply chain collaboration. *International Journal of Physical Distribution & Logistics Management*, 35(1),44-62.
- Sirmon, D. G., Gove, S., & Hitt, M. A. (2008). Resource management in dyadic competitive rivalry: The effects of resource bundling and deployment. *Academy of Management Journal*, 51(5), 919-935.
- Sirmon, D. G., Hitt, M. A., Ireland, R. D., & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *Journal of Management*, 37(5), 1390-1412.
- Sousa, R., & Voss, C. A. (2008). Contingency research in operations management practices. *Journal of Operations Management*, 26(6), 697-713.
- Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, 27(10), 1849-1867.
- Stewart, M., & Ivanov, D. (2019). Design redundancy in agile and resilient humanitarian supply chains. *Annals of Operations Research*, 1-27. DOI: 10.1007/s10479-019-03507-5.
- Swafford, P. M., Ghosh, S., & Murthy, N. (2006). The antecedents of supply chain agility of a firm: scale development and model testing. *Journal of Operations Management*, 24(2), 170-188.
- Tallon, P. P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizationorganisational agility: insights from a mediation model. *MIS Quarterly*, 35(2),463-486.

- Tan, K. C., Kannan, V. R., Hsu, C. C., & Leong, G. K. (2010). Supply chain information and relational alignments: mediators of EDI on firm performance. *International Journal of Physical Distribution & Logistics Management*, 40(5), 377-394.
- Tarafdar, M., & Qrunfleh, S. (2017). Agile supply chain strategy and supply chain performance: complementary roles of supply chain practices and information systems capability for agility. *International Journal of Production Research*, 55(4), 925-938.
- Tatham, P., & Rietjens, S. (2016). Integrated disaster relief logistics: a stepping stone towards viable civil–military networks?. *Disasters*, 40(1), 7-25.
- Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, 48(1), 159-205.
- Themistocleous, M., Irani, Z., & Love, P. E. (2004). Evaluating the integration of supply chain information systems: A case study. *European Journal of Operational Research*, 159(2), 393-405.
- Wang, Y., Niu, B., & Guo, P. (2013). On the advantage of quantity leadership when outsourcing production to a competitive contract manufacturer. *Production and Operations Management*, 22(1), 104-119.
- Wei, H. L., & Wang, E. T. (2010). The strategic value of supply chain visibility: increasing the ability to reconfigure. *European Journal of Information Systems*, 19(2), 238-249.
- Wang, Z., He, S. Y., & Leung, Y. (2018). Applying mobile phone data to travel behaviour research: A literature review. *Travel Behaviour and Society*, 11, 141-155.
- Wentz, L. (2006). Information and Communication Technologies for Civil-Military Coordination in Disaster Relief and Stabilization and Reconstruction In: Defense and Technology Paper. *Center for Technology and National Security Policy, National Defense University*.
- Wong, C. Y., & Karia, N. (2010). Explaining the competitive advantage of logistics service providers: A resource-based view approach. *International Journal of Production Economics*, 128(1), 51-67.
- Wu, F., Yenyurt, S., Kim, D., & Cavusgil, S. T. (2006). The impact of information technology on supply chain capabilities and firm performance: A resource-based view. *Industrial Marketing Management*, 35(4), 493-504.

Appendix A: Profile of the responding organisations (N=193)

Organisations	Frequency	Percentage
Developed-country government aid agencies	59	30.57
International NGOs	63	32.64
Volunteer, university and faith-based teams and individuals	54	27.98
Service providers and contractors	17	8.81
Nationality	Frequency	Percentage
<i>Asia</i>		
Afghanistan	4	2.07
Bangladesh	5	2.59
China	17	8.81
DPR Korea	6	3.11
India	13	6.74
Indonesia	3	1.55
Japan	13	6.74
Myanmar	4	2.07
Thailand	5	2.59
<i>Europe</i>		
Belgium	3	1.55
Denmark	6	3.11
France	11	5.70
Finland	7	3.63
Ireland	3	1.55
Netherlands	6	3.11
United Kingdom	8	4.15
<i>Africa</i>		
Cameroon	7	3.63
Egypt	3	1.55
South Africa	6	3.11
<i>North America</i>		
Canada	16	8.29
United States	15	7.77
Mexico	3	1.55
<i>South America</i>		
Argentina	12	6.22
Brazil	13	6.74

Appendix B: Operationalisation of Constructs

Construct and Derivation	Types	Measures
Artificial Intelligence driven Big Data Analytics Capability (AI-BDAC) (Adapted and modified from Dubey et al. 2019a)	Reflective	<p>We use artificial intelligence guided advanced analytical techniques (e.g. simulation, optimisation, regression) to improve decision-making related to joint disaster relief operations (AI-BDAC1)</p> <p>We use multiple data sources to improve collaboration during disaster relief efforts (AI-BDAC2)</p> <p>We use data visualisation techniques (e.g. dashboards) to assist users to decision-maker in understanding complex information (AI-BDAC3)</p> <p>We use dashboards to display information to undertake cause analysis and continuous improvement (AI-BDAC4)</p>
Information Alignment (IA) (Chan and Reich, 2007; Tan et al. 2010)	Reflective	<p>We use informal information sharing agreements among participating humanitarian organisations (IA1)</p> <p>We regularly communicate our future strategic needs to our service providers (IA2)</p> <p>We regularly communicate our future strategic needs among participating partners in disaster relief operations (IA3)</p> <p>We create compatible information systems among various humanitarian organisations (IA4)</p>
Collaboration (CO) (Krishnan et al. 2006; Moshtari, 2016)	Reflective	<p>The objectives for which the collaboration was established are being met (CO1)</p> <p>Our organisation is satisfied with the overall performance of the collaboration (CO2)</p> <p>Our association with these partners has been a successful one (CO3)</p> <p>These partners seem to be satisfied with the overall performance of the collaboration (CO4)</p>
Supply Chain Agility (SCAG) (Altay et al. 2018)	Reflective	<p>Our organisation can quickly detect changes in our environment (SCAG1)</p> <p>Our organisation can quickly sense threats in its environment (SCAG2)</p> <p>We make quick decisions to deal with changes in environment (SCAG3)</p>

Intergroup Leadership (IGL) (Hogg et al. 2012; Salem et al. 2019)	Reflective	<p>The field manager interacts frequently with both, local and expatriate employees (IGL1)</p> <p>The field manager puts lots of effort into strengthening the relationship between the local and expatriate group (IGL2)</p> <p>The field manager is a good example of the relationship between the local and expatriate group (IGL3)</p> <p>The field manager is an embodiment of the connection between the local and expatriate group (IGL4)</p> <p>The field manager stresses that local and expatriate employees work together while maintaining their distinct and separate group identities (IGL5)</p> <p>The field manager argues that the local and expatriate employees are two separate groups that need to work together collaboratively (IGL6)</p>
Interdependency (I) (Brown et al. 1995)	Reflective	<p>It would be costly for our organisation to lose its collaboration with the partner (I1)</p> <p>This partner would find it costly to lose the collaboration with our organisation (I2)</p>
Relationship Duration (RD) (Moshtari, 2016)	Formative	Time in years

Appendix C: Measures of inter-rater agreement

Constructs	Percentage method (%)	Ratio method	Inter-class correlation coefficient	Paired t-test
AI-BDAC	88	0.79	0.38	Not-significant
IA	85	0.76	0.43	Not-significant
CO	87	0.82	0.38	Not-significant
SCAG	84	0.83	0.33	Not-significant
IGL	83	0.73	0.29	Not-significant
I	91	0.79	0.32	Not-significant

Notes: AI-BDAC, Artificial Intelligence driven big data analytics capability; IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; IGL, Intergroup Leadership; I, Interdependency.

Appendix D: Model fit and quality indices (N=193)

Model fit and quality indices	Value from analysis	Acceptable if	Reference
APC	0.31, $p < 0.001$	$p < 0.05$	Rosenthal and Rosnow (1991)
ARS	0.512, $p < 0.001$	$p < 0.05$	
AVIF	3.504, $p < 0.001$	$p < 0.05$	Kock (2012)
Tenenhaus GoF	0.612	Large if ≥ 0.36	Tenenhaus et al. (2005)

Appendix E: R², Prediction and Effect Size (N=193)

CONSTRUCT	R ²	Q ²	F ² IN RELATION TO		
			IA	CO	SCAG
IA					
CO	0.32	0.18	0.21		
SCAG	0.83	0.88	0.27	0.72	

Notes: AI-BDAC, Artificial Intelligence driven big data analytics capability; IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility